LEUKEMIA DISEASE: OVERVIEW AND DETECTION APPROACHES

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Abstract: Leukemia, a complex hematologic malignancy, presents a formidable challenge in oncology due to its diverse subtypes and intricate diagnostic landscape. This paper provides an extensive literature review encompassing the classification of leukemia and exploration of various diagnostic approaches. Various methods such as blood tests, bone marrow aspiration, cytogenetic analysis, molecular testing, flow cytometry, and imaging tests are examined alongside recent advancements in diagnostic technologies. The review synthesizes studies highlighting the efficacy of innovative detection methodologies, including terahertz radiation, machine learning algorithms, deep learning models, and image processing techniques, in leukemia diagnosis.Furthermore, the paper presents an approach that utilizes pathological report analysing blood parameters and identifying correlations with different leukemia types using clustering techniques.

1. Introduction:

Cancer is characterized by uncontrolled cell growth, division, and invasion into other tissues due to genetic mutations. Mutated cells replicate uncontrollably, forming cancerous tissues responsible for further proliferation. Symptoms arise from cancerous cells invading other tissues, a process known as metastasis, spreading cancer throughout the body and impairing organ function. While cancer can affect individuals of any age, most types are more prevalent in older individuals due to accumulated DNA damage. Cancer is a leading cause of death in developed countries, driving extensive research in oncology for effective treatment strategies(https://en.wikipedia.org/wiki/Cancer).

There is no sure cure for cancer. It can only be cured if all of the cancerous cells are cut out or killed in place. This means that the earlier the cancer is treated, the better the chances are for a cure (because the cancer cells may not have had enough time to copy themselves and spread so much that the person cannot be cured).There are many different types of cancer, and each has its own symptoms and causes. Even with the same type of cancer, different people may have different symptoms, and may react to treatments differently; their cancer also may grow or spread at different speeds. Treatment has to be a good fit to both the type of cancer and the individual patient who has the cancer.

The paper is organized such that section 2 deals with Leukemia and WBC classes, section 3 emphasis literature review, section 4 presents proposed methodology followed by the conclusion.

2. Leukemia

Leukemia, or leukaemia, denotes a malignancy affecting white blood cells and bone marrow, characterized by an overproduction of leukocytes. Its severity and prognosis vary depending on the leukemia subtype. In 2000, approximately 256,000 individuals globally developed leukemia, with about 209,000 succumbing to the disease. The majority of cases, around 90%, occur in adults(https://en.wikipedia.org/wiki/Leukemia).

Blood comprises various types of cells, including white blood cells (monocytes, lymphocytes, neutrophils, eosinophils, basophils, and macrophages), red blood cells (erythrocytes), and platelets.

White blood cells are produced by different tissues in the body. Around 60 to 70 percent of white cells, known as granulocytes, are generated in the bone marrow in adults. Lymphocytes, accounting for 20 to 30 percent, are produced in lymphatic tissues like the thymus, spleen, and lymph nodes. Monocytes, comprising 4 to 8 percent of white cells, are produced in reticuloendothelial tissues such as the spleen, liver, and lymph nodes. An average healthy adult has between 4,500 and 11,000 white blood cells per cubic millimetre of blood, with fluctuations occurring throughout the day.

2.1 WBC Classes

White blood cells are categorized into major classes:

Lymphocytes, further divided into B cells and T cells, play a crucial role in recognizing and eliminating foreign agents from the body. B lymphocytes produce antibodies to destroy foreign microorganisms, while T cells identify and destroy virally infected or cancerous cells. Natural killer (NK) cells also contribute to this process.

Granulocytes, the most abundant white cells, combat large pathogens like protozoans and helminths, and play a role in allergy and inflammation. They contain cytoplasmic granules with potent chemicals and are subdivided into neutrophils, eosinophils, and basophils based on their dye uptake in the laboratory.

Monocytes, constituting 4 to 8 percent of white blood cells, transform into macrophages at sites of infection. Macrophages act as scavengers, phagocytosing microorganisms and cellular debris, and play a key role in the immune response by presenting antigens to T lymphocytes. Figure2.1 summarizes various classification of WBC(https://en.wikipedia.org/wiki/White_blood_cell).

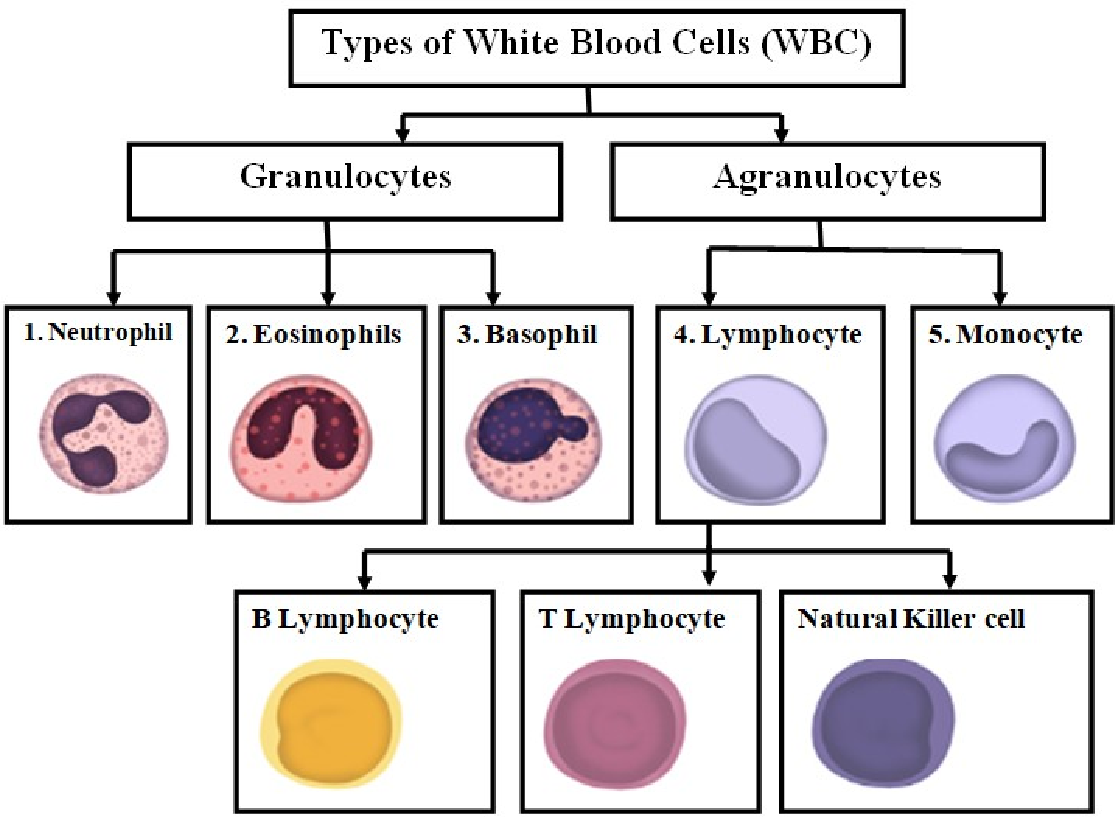

Figure 2.1: WBC Classification

Acute type of Leukemia shows rapid growth or spread of cancer. Chronic type of Leukemia shows slow growth or spread of cancer. ALL- Acute Lymphoblastic Leukemia. Common in children and more in male. It indicates Non-specific esterase (NSE). Symptoms have low HB and platelets. There is presence of lymphoblast. AML- Acute myeloblastic Leukemia Common in adults. There is presence of Auer rods in blast cells. It indicates Non-specific esterase (NSE). Symptoms have low platelets. There is presence of myeloblast cells. CLL- Chronic lymphoblastic Leukemia. It indicates slow progression. It's mostly seen in 60 years and above WBC count is high. Platelets count low. There will be presence of smear cells. CML- Chronic myeloblastic Leukemia. There is presence of myeloid cells. WBC has Neutrophil, Monocyte, Basinophil and Eosinophil. High WBC count in blood report.

ALL is characterized by the rapid proliferation of immature lymphocytes, leading to symptoms such as fatigue, pale skin, fever, bruising, and enlarged lymph nodes. CLL, on the other hand, is marked by excessive lymphocyte production, often progressing gradually over years. Initial stages may be asymptomatic, while later stages may manifest as non-painful lymph node swelling, fatigue, fever, night sweats, or weight loss. AML involves the rapid growth of abnormal myeloid cells, leading to symptoms like fatigue, shortness of breath, bruising, and increased infection risk. Diagnosis typically involves bone marrow aspiration and specific blood tests.

Treatment for leukemia varies depending on the subtype and individual factors. Chemotherapy is commonly used to induce remission, followed by additional therapies such as radiation or stem cell transplant. Targeted therapies may also be employed based on genetic mutations present in the cancer cells. Overall, collaborative efforts among researchers, clinicians, and patients are essential in improving outcomes and advancing leukemia treatment strategies.

3. Literature Review

In the diagnosis of leukemia, a variety of diagnostic techniques are utilized to accurately identify different types of the Leukemia types. These methods encompass:

1. Blood Tests: Complete blood count (CBC) and peripheral blood smear examination to identify abnormal blood cell counts and morphology.
2. Bone Marrow Aspiration and Biopsy: Direct examination of bone marrow cells for abnormalities in cell morphology and proliferation.
3. Cytogenetic Analysis: Examination of chromosomal abnormalities, such as translocations, using techniques like karyotyping and fluorescence in situ hybridization (FISH).

4. Molecular Testing: Polymerase chain reaction (PCR) to detect specific genetic mutations, like BCR-ABL1 in chronic myeloid leukemia (CML) or FLT3 mutations in acute myeloid leukemia (AML).
5. Flow Cytometry: Immunophenotyping of leukemia cells based on cell surface markers to classify leukemia subtypes and assess their immunophenotypic profiles.
6. Imaging Tests: X-rays, computed tomography (CT), magnetic resonance imaging (MRI), or positron emission tomography (PET) scans to detect organ enlargement or infiltration by leukemia cells.

Each method has its advantages and may be used alone or in combination to achieve an accurate diagnosis of leukemia. We have presented a brief review of the same in the below section.

Cheon et al. [1] used terahertz radiation to detect and manipulate DNA methylation in blood cancer cell lines, suggesting its potential in cancer treatment. Xing and Yilin [2] enhanced the KNN algorithm for medical health big data classification, improving efficiency and accuracy. Safuan et al. [3] proposed a CNN algorithm to automate White Blood Cell (WBC) detection, with VGG showing superior performance.

Nighat et al. [4] introduced an IoMT-based framework for leukemia detection, enabling real-time testing and diagnosis. Jabeen et al. [5] developed a method for early leukemia detection using image analysis, offering a rapid, cost-effective alternative. Hossain et al. [6] proposed a Faster-RCNN-based system for early leukemia detection in Bangladesh, integrating with smartphones for rural areas. Genovese et al. [7] introduced a machine learning-based approach for enhancing blood sample images and classifying ALL from normal samples.

Pałczyński et al. [8] developed an optimized neural network architecture for acute lymphoblastic leukemia diagnosis, achieving high accuracy.Aftab et al. [9] focused on Acute Leukemia detection using deep transfer learning, achieving high accuracy. Atteia et al. [10] introduced a Bayesian-optimized CNN for acute lymphoblastic leukemia detection, achieving superior classification accuracy.

Zhong et al. [11] developed an AI model for acute leukemia diagnosis using multiparameter flow cytometry, showing promising clinical application.Genovese et al. [12] presented a method for detecting ALL using histopathological transfer learning, showing enhanced accuracy. Khademi et al. [13] explored nanotechnology-based diagnostics and therapeutics for acute lymphoblastic leukemia, revealing promising applications.

Desi et al. [14] introduced an automated optical image processing system for blood disorder identification, enhancing accuracy and processing time.Hossain et al. [15] focused on early leukemia prediction using a supervised machine learning model, achieving high accuracy. Armya et al. [16] assessed leukemia detection using machine learning classifiers, with Naïve Bayes showing the highest accuracy. Diana et al. [17] automated leukocyte classification using deep learning, surpassing the Naive Bayes Classifier in accuracy. Jusman et al. [18] developed a system program for early leukemia detection using image processing, achieving high accuracy. Kumar et al. [19] utilized microscopy image processing software for acute lymphoblastic leukemia detection, enhancing diagnostic accuracy.

Della et al. [21] investigated various molecular methods for minimal residual disease evaluation in acute lymphoblastic leukemia, suggesting potential advantages of new molecular approaches.Varadarajan et al. [22] explored novel therapeutic approaches for relapsed acute lymphoblastic leukemia post allogeneic hematopoietic cell transplantation in adult patients.

Hoffmann et al. [23] developed Cinderella, an XAI method for measuring haemodilution and minimal residual disease in acute myeloid leukemia.

Devi et al. [24] introduced the GBHSV-Leuk method for acute lymphoblastic leukemia detection, achieving high accuracy.Hossain et al. [25] proposed a supervised machine learning model for leukemia detection, achieving high accuracy and generating explainable rules. Ananth et al. [26] developed a small image processing method for leukemia detection, showing greater effectiveness than previous methods. Sridhar et al. [27] employed deep learning techniques for early leukemia detection, achieving notable accuracy.

Das et al. [28] systematically analysed segmentation and classification approaches for acute lymphoblastic leukemia detection, emphasizing the efficacy of deep learning. Hoffmann et al. [29] investigated the potential of MPFC data from chronic lymphocytic leukemia samples to predict outcomes using XAI. Molin et al. [30] developed CircFusion, a software tool for detecting linear fusion transcripts and f-circRNAs in cancer cells with rearranged genomes.

Hoffmann Khalil et al. [31] studied CD200 expression in leukemic B cells and its correlation with clinical findings in acute lymphoblastic leukemia patients. Liu [32] explored SETD2 expression in acute myeloid leukemia patients, revealing its association with treatment response and survival outcomes.

Tiago et al. [33] highlighted the potential of DNA methylation-based tests in molecular cancer early detection (MCED), particularly in combination with AI. Pier et al. [34] examined the relationship between physical activity and mental health outcomes among adolescents during the COVID-19 pandemic. Mansoor et al. [35] investigated gamma-tocotrienol as a potential inhibitor for the BCR-ABL1 fusion protein in leukemia therapy.

Sakthivel et al. [36] proposed an approach for classifying Acute Lymphoblastic Leukemia (ALL) and Multiple Myeloma (MM) using image processing techniques. Rawal et al. [37] fabricated Ag/Au thin film electrodes for monitoring serum albumin levels as a prognostic biomarker for blood cancer.The summary of the same has been provided in the table 3.1.

Table 3.1: Literature Review Summary

SI.NO. (References)	TITLE	SAMPLE COLLECTION	TECHNIQUES/METHODS	TYPES OF LEUKEMIA	ACCURACY
[1]	Detection and manipulation of methylation in blood cancer DNA using terahertz radiation	BLOOD	Terahertz radiation andTerahertz time-domain spectroscopy	Blood cancer	10% to 70%
[2]	Medical Health Big Data Classification Based on KNN Classification Algorithm	Hospital, Public health and community healthcare data base	KNN algorithm based oncluster denoising and density cropping	Blood cancer	Single-category classi cation and multi-category classification
[3]	Investigation of white blood cell biomarker model for acute lymphoblastic leukemia detection based on convolutional neural network	Immature White Blood Cells (WBCs) called lymphoblast	Convolutional Neural Network (CNN)	Acute Lymphoblastic Leukemia (ALL)	99.13%
[4]	IoMT-Based Automated Detection and Classification of Leukemia Using Deep Learning	Bone marrow and/or blood	Dense Convolutional Neural Network (DenseNet-121) and Residual Convolutional Neural Network (ResNet-34)	Acute or chronic Leukemia & ALL, AML	99.91% and 99.96%
[5]	Leukemia Detection Mechanism through Microscopic Image and ML Techniques	Blood components (Neutrophils, Eosinophils, Basophils, Lymphocytes and Monocytes)	Faster-RCNN machine learning algorithm	Acute Lymphocytic Leukemia (ALL)	90%
[6]	Acute lymphoblastic leukemia detection based on adaptive un-sharpening and deep learning	Peripheral blood samples	Deep Learning, CNN	Acute Lymphoblastic (or Lymphocytic) Leukemia (ALL)	96.84%

[7]	Executing Spark BigDL for Leukemia Detection from Microscopic Images using Transfer Learning	Bone marrow & blood cells	1. BigDL library using apache spark framework 2. Convolutional Neural Network (CNN) architecture GoogleNet deep transfer learning	Acute Myeloid Leukemia (AML), Actuate Lymphocytic Leukemia (ALL), Chronic Myeloid Leukemia (CML) and Chronic Lymphocytic Leukemia (CLL)	1)97.33% and 94.78% 2)96.42% and 92.69%
[8]	Histopathological Transfer Learning for Acute Lymphoblastic Leukemia Detection	Blood samples	1) BigDL library using apache spark framework 2) CNN deep learning model Deep Learning, CNN Transfer Learning, Histopathology	Acute Lymphoblastic (or Lymphocytic) Leukemia (ALL)	1)97.33% and 94.78% 2)96.42% and 92.69% training and validation
[9]	IoT Application of Transfer Learning in Hybrid Artificial Intelligence Systems for Acute Lymphoblastic Leukemia Classification	Bone marrow	MobileNet v2 encoder pre-trained on the ImageNet dataset and machine learning algorithms, XGBoost, Random Forest, and Decision Tree algorithms	Acute lymphoblastic leukemia	97.4%.
[10]	BO-ALLCNN: Bayesian-Based Optimized CNN for Acute Lymphoblastic Leukemia Detection in Microscopic Blood Smear Images	Lymphocytes in the blood or bone marrow, blood smear	Bayesian-based optimized convolutional neural network (CNN)	Acute lymphoblastic leukemia (ALL)	100%
[11]	Diagnosis of Acute Leukemia by Multiparameter Flow Cytometry with the Assistance of Artificial Intelligence	Peripheral blood (PB) and bone marrow (BM) specimens, and cytogenetic and molecular data	AI assisted multiparameter flow cytometry (MFC) diagnosis	Acute leukemia	Not mentioned
[12]	Analysis of IoT based Leukemia Detection Techniques	Blood cells (leucocytes)	Convolutional neural networks (CNNs), deep learning, image processing, and machine learning	Acute lymphoblastic leukemia (ALL)	Not mentioned
[13]	Diagnosis of Acute Leukemia by Multiparameter Flow Cytometry with the Assistance of Artificial Intelligence	Peripheral blood (PB) and bone marrow (BM) specimens, and cytogenetic and molecular data	AI assisted multiparameter flow cytometry (MFC) diagnosis	Acute leukemia	Not mentioned
[14]	Identification of critical hemodilution by artificial intelligence in bone marrow assessed for minimal residual disease analysis in acute myeloid leukemia: The Cinderella method	Bone marrow (BM) & peripheral blood (PB)	Explainable artificial intelligence (XAI) Cinderella, flow cytometry	Acute myeloid leukemia	Not mentioned
[15]	A Systematic Literature Review on Leukemia Prediction Using Machine Learning	Marrow of bones	Machine Learning	Leukemia	Not mentioned

[16]	An Advanced Low-cost Blood Cancer Detection System	Blood Cancer, white blood cells, immature cells	Histogram levelling, Thresholding, straight difference expanding, and morphological techniques	Blood Cancer	Not mentioned
[17]	Enhanced Machine learning algorithms Lightweight Ensemble Classification of Normal versus Leukemic Cells	Blood, bone marrow	Machine learning algorithms, conventional neural network topologies, computer-aided diagnostic (CAD) models, deep learning model , ML calculations, especially DL, in CAD frameworks, entire slide imaging (WSI)	leukemia	Not mentioned
[18]	A Systematic Review on Recent Advancements in Deep and Machine Learning Based Detection and Classification of Acute Lymphoblastic Leukemia	Bone marrow and affects white blood cells (WBCs)	Deep and machine learning-based, artificial intelligence , signal and image processing-based techniques, conventional machine learning-based techniques, and deep learning-based techniques, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and the Autoencoder	Acute Lymphoblastic Leukemia	Not mentioned
[19]	Symptom Based Explainable Artificial Intelligence Model for Leukemia Detection	Bone marrow & blood cells	Machine learning model, explainable supervised model,Apriori algorithm, decision tree model proposed in our experiments has achieved 97.45% of accuracy, 0.63 of Mathew's Correlation Coefficient (MCC) and 0.783 of area under Receiver Operating Characteristic (ROC) curve on the test set.	Leukemia	Not mentioned
[20]	Gaussian Blurring Technique for Detecting and Classifying Acute Lymphoblastic Leukemia Cancer Cells from Microscopic Biopsy Images	Peripheral blood samples	Gaussian Blurring Technique, GBHSV-Leuk method	Acute Lymphoblastic Leukemia Cancer	Not mentioned
[21]	Optimizing Molecular Minimal Residual Disease Analysis in Adult Acute Lymphoblastic Leukemia	Neoplastic cells, blood components	MRD in ALL are polymerase chain reaction (PCR) amplification-based approaches	Adult Acute Lymphoblastic Leukemia	Not mentioned
[22]	Post-Hematopoietic Cell Transplantation Relapsed Acute Lymphoblastic Leukemia: Current Challenges and Future Directions	T-cell	Allogeneic hematopoietic cell transplantation (allo-HCT), cellular immunotherapy	Acute Lymphoblastic Leukemia	Not mentioned

[23]	Prediction of Clinical Outcomes with Explainable Artificial Intelligence in Patients with Chronic Lymphocytic Leukemia	Genetic analysis	Artificial intelligence; ALPODS; flow cytometry	Chronic Lymphocytic Leukemia	CD4+ T-cell population enhanced the predictive ability of the CLL-IPI (AUC 0.83; 95% CI 0.77–0.90; $p < 0.0001$).
[24]	Prognostic Role of CD200 in Acute Lymphoblastic Leukemia Patients	Complete blood count , BM aspiration, immunophenotyping of blast cells, and CD200 expression	CD200 expression shows a significant correlation with total leucocytic count and haemoglobin level ($p = 0.001$, 0.03, respectively).	Acute Lymphoblastic Leukemia	Not mentioned
[25]	SETD2 detection may reveal response to induction therapy and survival profile in acute myeloid leukemia patients	Bone marrow (BM) samples	SETD2 expression with disease risk, features, treatment response, and survival profile, CD200 expression shows a significant correlation with total leucocytic count and haemoglobin level ($p = 0.001$, 0.03, respectively).	Acute myeloid leukemia	Not mentioned
[26]	Shifting the Cancer Screening Paradigm: The Rising Potential of Blood-Based Multi-Cancer Early Detection Tests	Tumor-related markers	Multicancer early detection (MCED) tests, artificial intelligence, liquid biopsy; biomarkers, DNA methylation-based tests	Cancer	Not mentioned
[27]	Updating the Clinical Application of Blood Biomarkers and Their Algorithms in the Diagnosis and Surveillance of Hepatocellular Carcinoma: A Critical Review	Tumor biomarkers	α-FP biomarker with/without ultrasonography, combining α-FP with novel biomarkers can enhance HCC detection sensitivity, Lens culinaris agglutinin-reactive fraction of Alpha-fetoprotein (α-FP), α-FP-L3, Des-γ-carboxy-prothrombin (DCP or PIVKA-II), and the GALAD score, are being used more frequently in the diagnosis and prognosis of HCC	Hepatocellular Carcinoma, liver cancer is hepatocellular carcinoma (HCC)	Not mentioned
[28]	Antigen Receptors Gene Analysis for Minimal Residual Disease Detection in Acute Lymphoblastic Leukemia: The Role of High Throughput Sequencing.	Residual leukemic blast prognostic indicator, minimal residual disease	High throughput sequencing (HTS), MRD monitoring with emphasis on the use of HTS	Acute Lymphoblastic Leukemia	Not mentioned

[29]	Artificial Intelligence Assisted Pharmacophore Design for Philadelphia Chromosome-Positive Leukemia with Gamma-Tocotrienol: A Toxicity Comparison Approach with Asimina	Philadelphia chromosome, high level Ph+	Deep learning artificial intelligence (AI) drug design, AIGT's (Artificial Intelligence Gamma-Tocotrienol) drug-likeliness analysis	Chronic Myeloid Leukemia (CML)	Not mentioned
[30]	Discovery of fusion circular RNAs in leukemia with KMT2A::AFF1 rearrangements by the new software CircFusion	Chromosomal translocations in cancer genomes	Genomes with chromosomal rearrangements, fusion circular RNAs (f-circRNAs), PML::RARα and KMT2A::MLLT3	Leukemia	Not mentioned
[31]	Electrochemical and Optical Analysis of Various Compositions of Au and Ag Layers for Blood Cancer Prognosis	Prognostic biomarker of blood	Electrochemical and optical analysis, Ag/Au thin film electrode	Leukemia	Not mentioned
[32]	An Optimized Single Nucleotide Polymorphism-Based Detection Method Suggests That Allelic Variants in the 3'Untranslated Region of RRAS2 Correlate with Treatment Response in Chronic Lymphocytic Leukemia Patients	RS8570 position in the 3'-untranslated region of RRAS2	Single qPCR method, RRAS2 Correlate, polymerase chain reaction (PCR)	Chronic Lymphocytic Leukemia	Not mentioned
[33]	Machine Learning Driven Dashboard for Chronic Myeloid Leukemia Prediction using Protein Sequences	Protein Sequences, hematopoietic progenitor cells, mutated genes like BCL2, HSP90, PARP, and RB	Machine Learning and Data Science, feature extraction of Di-peptide Composition (DPC), Amino Acid Composition (AAC), and Pseudo amino acid composition (Pse-AAC), Support Vector Machine (SVM), XGBoost, Random Forest (RF), K Nearest Neighbour (KNN), Decision Tree (DT), and Logistic Regression (LR)	Chronic Myeloid Leukemia	94%
[34]	Automated Leukemia Screening and Sub-types Classification Using Deep Learning	Blood and bone marrow, complete blood count test	FAB classification, i.e., L1, L2, and L3 types, microscopic inspection of blood smears and bone marrow aspiration	Leukemia and ALL	96.06%
[35]	Hematologic Cancer Detection Using White Blood Cancerous Cells Empowered with Transfer Learning and Image Processing	Immature lymphocytes, monocytes, neutrophils, and eosinophil cells	Deep learning,AlexNet, MobileNet, and ResNet	Lymphoma and Leukemia	97.30%

[36]	Applications of Machine Learning in Chronic Myeloid Leukemia	Myeloid cells in the bone marrow, neutrophils	Artificial intelligence; chronic myeloid leukemia; machine learning; convolutional neural networks; hemoglobinopathies	Chronic myeloid leukemia (CML)	Not mentioned
[37]	Automated Acute Lymphoblastic Leukemia Detection Using Blood Smear Image Analysis	Blood cells of bone marrow	Image processing and artificial intelligence methods. Machine learning– and deep learning	Acute lymphoblastic leukemia (ALL)	Not mentioned

4. Proposed methodology

In our proposal approach, we outline a methodology for analysing blood reports sourced from the pathological department, focusing on various blood parameters to discern correlations with different types of blood cancers, such as Chronic Myeloid Leukemia (CML), Acute Myeloid Leukemia (AML), Non-Hodgkin's Lymphoma (NHL), and Normal Leukocyte (NL). Our proposed method leverages the clustering concept of the K-means algorithm to conduct an in-depth analysis aimed at identifying similarities among these parameters for each type of blood cancer. By employing this approach, we aim to group similar features together, providing valuable insights into potential patterns and relationships within the dataset.The proposed methodology is illustrated in the Figure4.1.

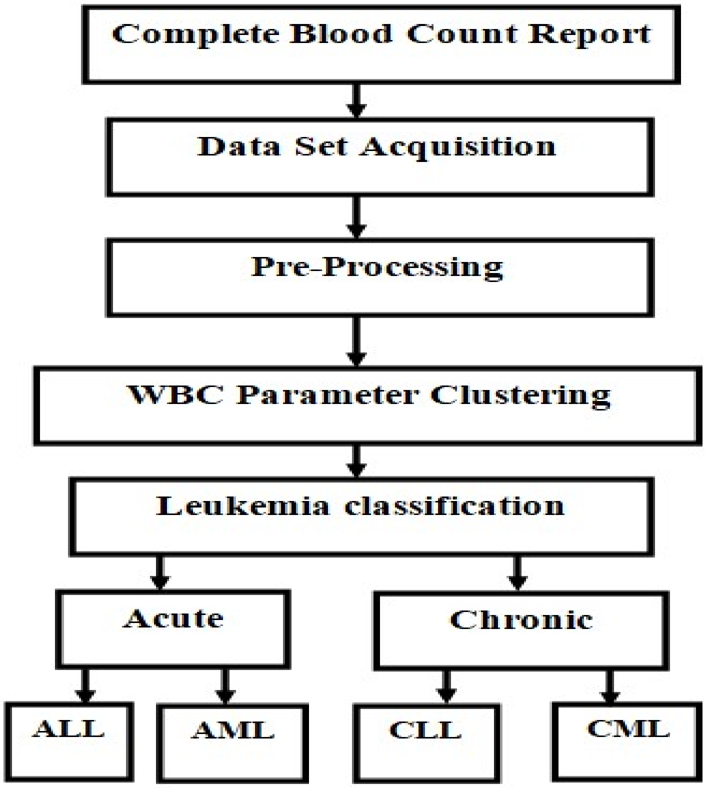

Figure 4.1: Proposed methodology for Leukemia classification

5. Conclusion: Blood cancerposes unique challenges due to its varied subtypes and diagnostic intricacies. This paper has tried to present an overview of leukemia classification and diagnostic methodologies, evaluating various detection approaches, and presented research contributions. The literature review analysed traditional diagnostic techniques alongside recent advancements such as terahertz radiation and machine learning algorithms, stating their potential in enhancing diagnostic accuracy. Furthermore, we are proposing an approach that utilizes clustering techniques to uncover patterns within the dataset, aiming to provide insights that could potentially enhance patient outcomes and inform treatment strategies.

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